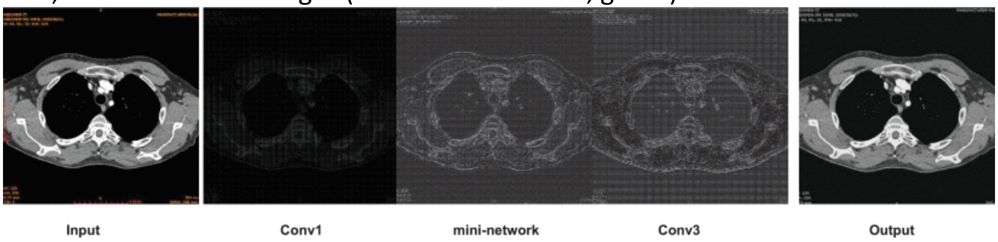
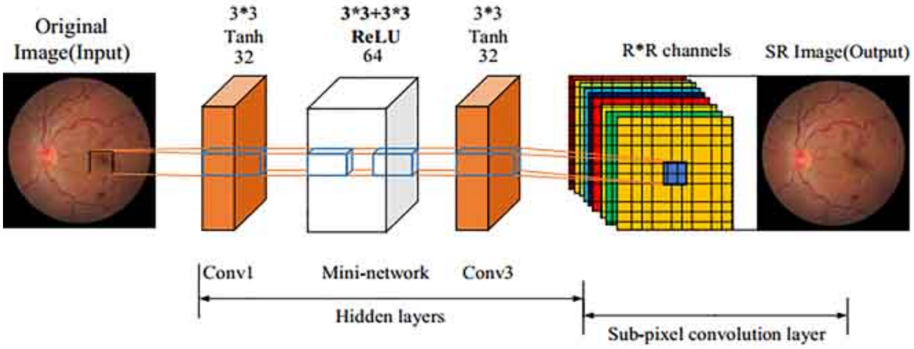
Summary of papers on super-resolution with medical images:

Paper 1. A Fast Medical Image Super Resolution Method Based on Deep Learning Network

- Link
- **Images:** Retinal, Brain and Bone images (3 channels red blue, green)



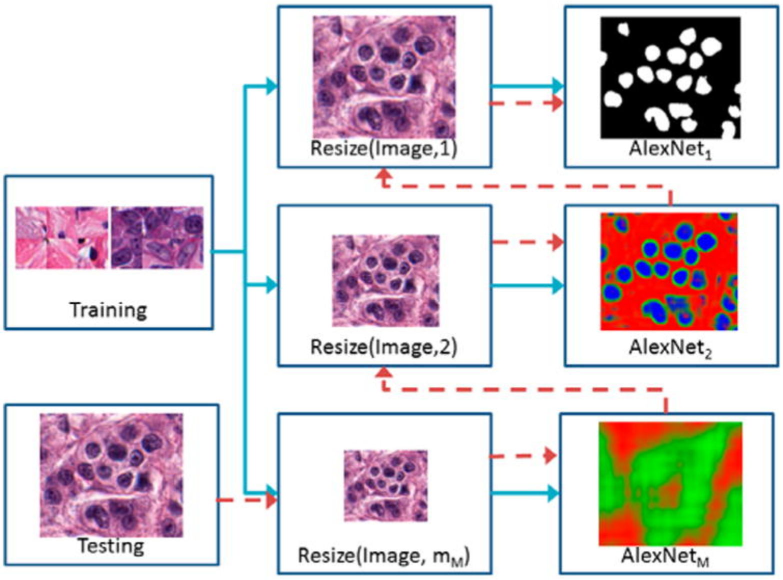
- **Network :** 3 components → sub-pixel convolutional layer + mini-network and hidden layers.



Sub-pixel and mini network designed to shorten time of super-resolution.

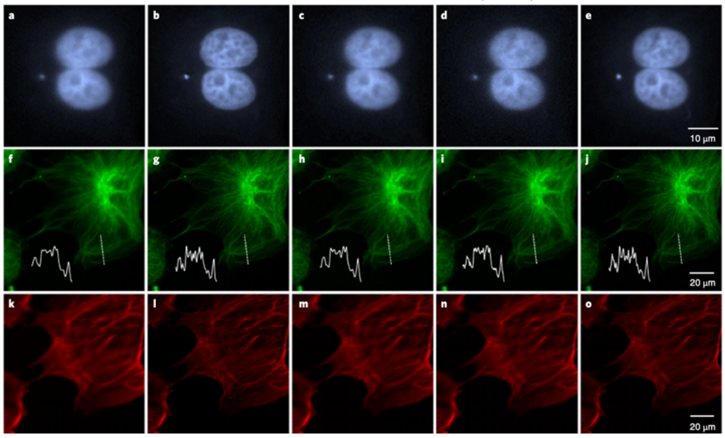
Paper 2. (from the link you sent me) A resolution adaptive deep hierarchical (RADHical) learning scheme applied to nuclear segmentation of digital pathology images

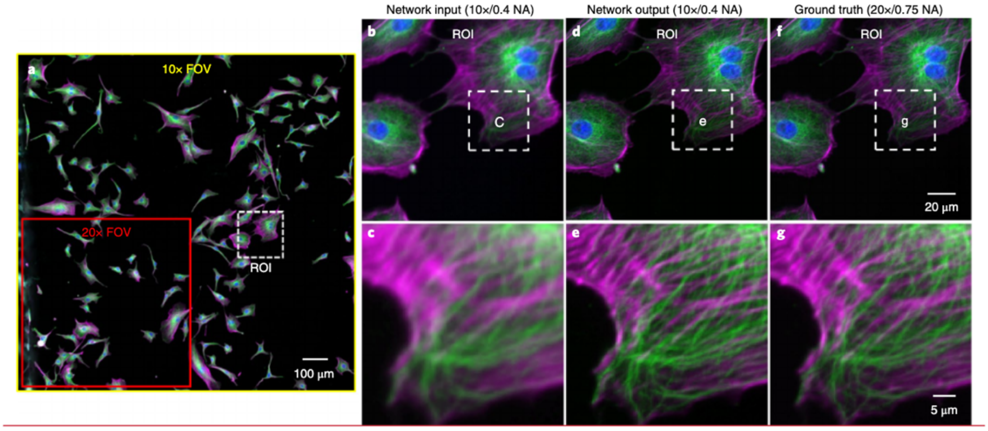
- **Link**
- **Images:** breast cancer images
- **Approach:** resolution adaptive hierarchical learning scheme where DL networks at lower resolution are leveraged to determine if higher levels of magnification are necessary to provide results of nuclear segmentation → so actually no high resolution creation here because I think the images are already in HR.



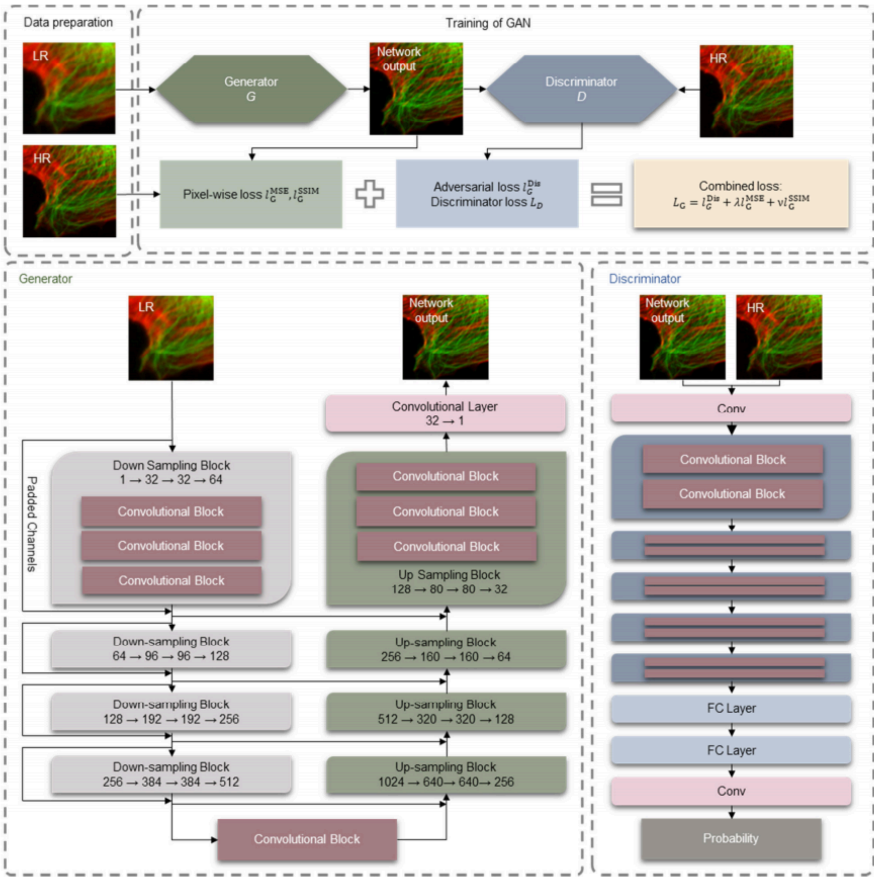
Paper 3. Deep Learning enables cross-modality super-resolution in fluorescence microscopy

- **Link for paper and additionnal information**
- **Images:** TIRF microscopy images of subcellular structures within cells and tissues





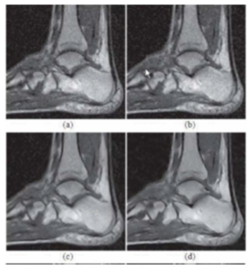
- **Network:** GAN Network



Supplementary Figure 13

The training process and the architecture of the generative adversarial network (GAN) that we used for image super-resolution.

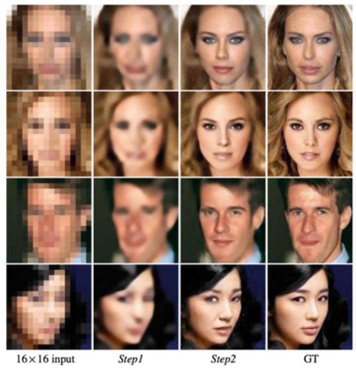
Paper 4. Super Resolution Techniques for Medical Processing



- [Link]
- Gives a summary of all available techniques but no precise network. Also, again images provided are more bone-like.

- **Simple approaches:** Conventional interpolation methods (nearest neighbor, bilinear and bicubic interpolations) and more sophisticated methods using sparse-coding super-resolution algorithms find a sparse representation and enable a super-resolution gain (dictionary learning)

Paper 5. Deep CNN Denoiser and Multi-Layer Neighbor Component Embedding for Face Hallucination



- [Link]
- Proposes solution for tiny LR images → general face hallucination method integrating model-based optimization and discriminative inference. Deep CNN denoiser prior is plugged into super-resolution optimization model with the aid of image-adaptive Laplacian regularization.
- **Images**:
- **Network**:
  - Step 1: Deep CNN denoiser based global face reconstruction
  - Step 2: MNCE based residual compensation

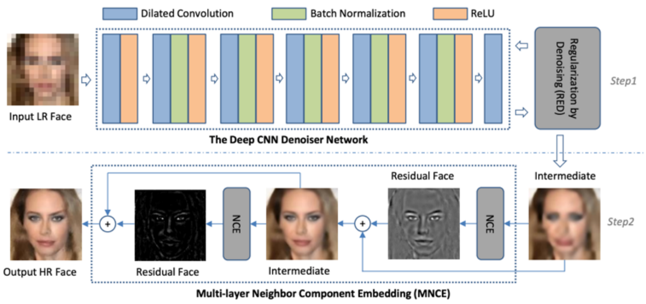


Figure 2: Main steps of the proposed face hallucination algorithm. *Step1*: Deep CNN denoiser based global face reconstruction. *Step2*: MNCE based residual compensation. For convenience, here we only show two layer NCE.

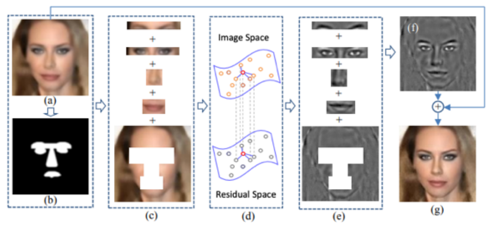
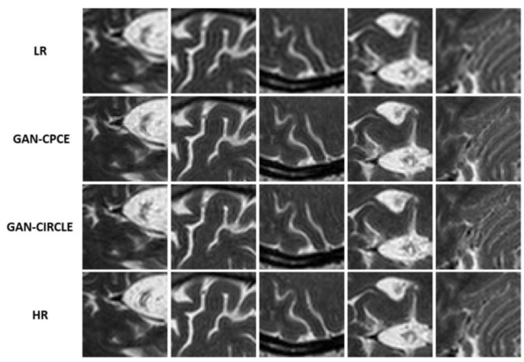


Figure 3: Illustration of neighbor component embedding based residual compensation. (a) Input image. (b) Face component masks. (c) Five facial components. (d) Neighbor embedding on the image and residual manifold spaces. (e) Constructed residual components. (f) Residual face image. (g) Hallucinated face image.

Paper 6. Super-resolution MRI through Deep Learning



- [Link]
- **Images:**
- **Network:** Adapt two networks for CT to MRI → path-based convolutional encoder-decoder with VGG (GAN-CPCE) and GAN constrained by the identical, residual and cycle learning ensemble (GAN-CIRCLE)

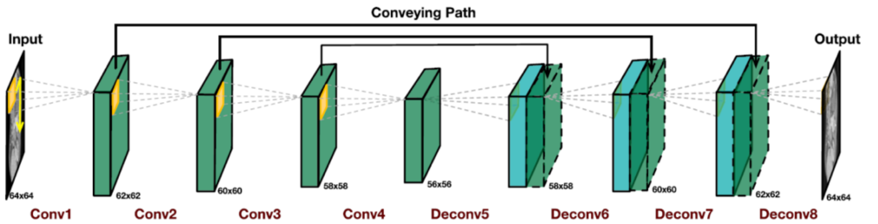


Fig. 1. The structure of the generator of GAN-CPCE from [23]. For info on the whole network, please read [23].

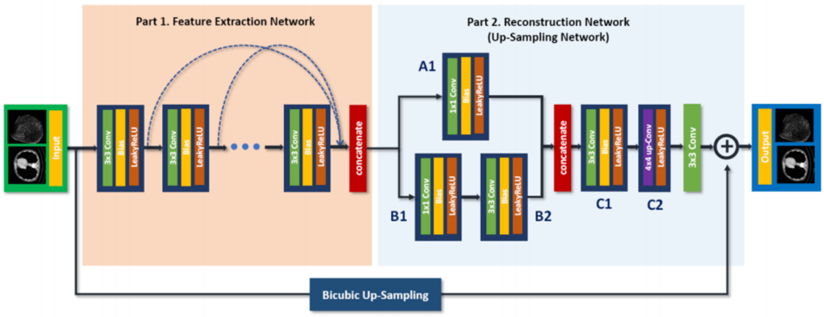


Fig. 2. The structure of the generator in the GAN-CIRCLE, copied from [26].

Paper 7. Image Super-resolution Using Deep Convolutional Networks

- Link
- **Images**
- **Network:** SRCNN convolutional network that directly learns an end-to-end mapping between low- and high-resolution images. Pipeline:
  - overlapping patches densely cropped from the input image and pre-processed so that each patch is a high-dimensional vector
  - non-linear mapping of high-dim vectors to another high-dimensional vector
  - reconstruction : aggregation of high-resolution patch-wise representations to generate final HR image

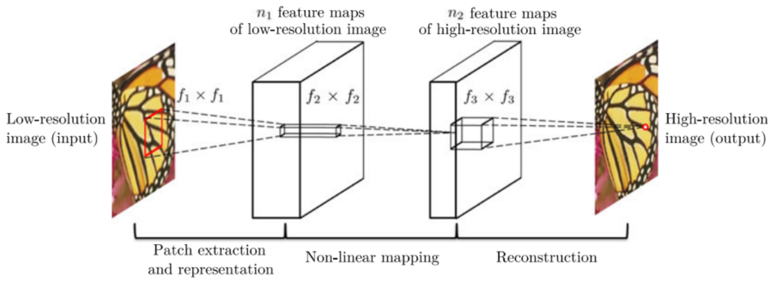


Fig. 2. Given a low-resolution image $\mathbf{Y}$, the first convolutional layer of the SRCNN extracts a set of feature maps. The second layer maps these feature maps nonlinearly to high-resolution patch representations. The last layer combines the predictions within a spatial neighbourhood to produce the final high-resolution image $F(\mathbf{Y})$.

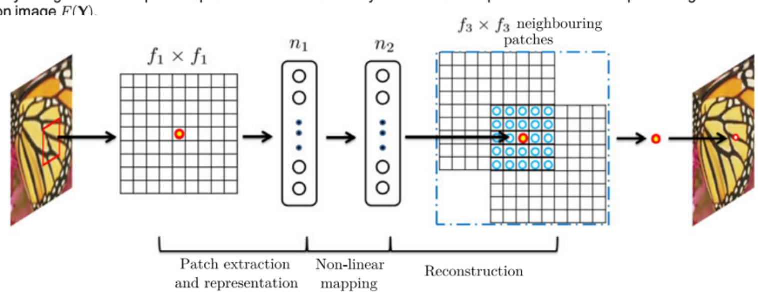


Fig. 3. An illustration of sparse-coding-based methods in the view of a convolutional neural network.

Paper 8. Super-Resolution of MRI Images via Convex Optimization with Local and global prior regularization and spectrum fitting

- Link
- Convex optimization formulation (no CNN)

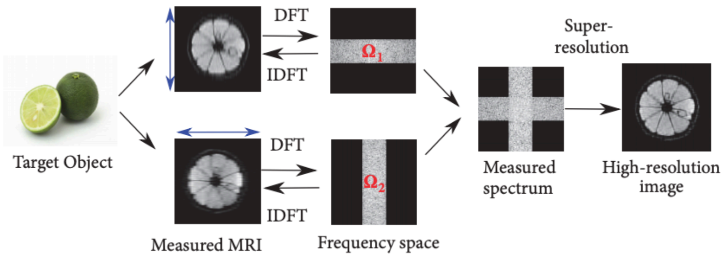


FIGURE 1: Flow of MR image acquisition and super-resolution. The specimen is measured anisotropically from different directions. The blue arrows denote the through-slice directions. MR images are obtained with a narrow bandwidth along the through-slice directions. In most MR images, the spatial resolution along the through-slice direction is more than three times lower than that in the other two directions. There are still unknown high-frequency components even when a number of measurements are available. These components are completed by super-resolution.